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ARTICLE

Multi-Modal Named Entity Recognition with Auxiliary Visual Knowledge and Word-Level Fusion

Huansha Wang*, **Ruiyang Huang***, **Qinrang Liu and Xinghao Wang**

National Digital Switching System Engineering & Technological R&D Center, Information Engineering University, Zhengzhou, 450001, China

*Corresponding Authors: Huansha Wang. Email: whs123@mail.ustc.edu.cn; Ruiyang Huang. Email: gisexpert@163.com

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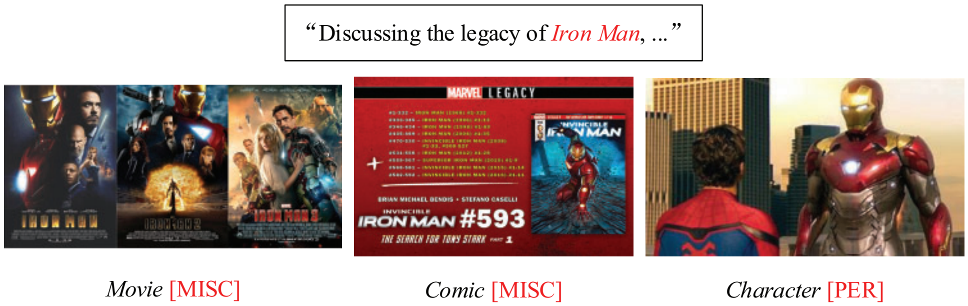
ABSTRACT: Multi-modal Named Entity Recognition (MNER) aims to better identify meaningful textual entities by integrating information from images. Previous work has focused on extracting visual semantics at a fine-grained level, or obtaining entity related external knowledge from knowledge bases or Large Language Models (LLMs). However, these approaches ignore the poor semantic correlation between visual and textual modalities in MNER datasets and do not explore different multi-modal fusion approaches. In this paper, we present MMAVK, a multi-modal named entity recognition model with auxiliary visual knowledge and word-level fusion, which aims to leverage the Multi-modal Large Language Model (MLLM) as an implicit knowledge base. It also extracts vision-based auxiliary knowledge from the image for more accurate and effective recognition. Specifically, we propose vision-based auxiliary knowledge generation, which guides the MLLM to extract external knowledge exclusively derived from images to aid entity recognition by designing target-specific prompts, thus avoiding redundant recognition and cognitive confusion caused by the simultaneous processing of image-text pairs. Furthermore, we employ a word-level multi-modal fusion mechanism to fuse the extracted external knowledge with each word-embedding embedded from the transformer-based encoder. Extensive experimental results demonstrate that MMAVK outperforms or equals the state-of-the-art methods on the two classical MNER datasets, even when the large models employed have significantly fewer parameters than other baselines.

KEYWORDS: Multi-modal named entity recognition; large language model; multi-modal fusion

1 Introduction

With the emergence of image-text pairs in social media and web applications, the field of multi-modal named entity recognition (MNER) has witnessed remarkable advancements, capturing significant research interest. Compared with the traditional uni-modal named entity recognition based on textual features, MNER models can provide intuitive visual features by extracting the image semantics associated with the textual entities. This improves the effectiveness of entity recognition [1]. As shown in Fig. 1, the attachment of a distinct descriptive image to the same text will result in a change in the outcomes of entity recognition. The traditional processing paradigm for multi-modal tasks is to first process image and text data based on one or more encoders to extract the corresponding low-dimensional embeddings. Subsequently, joint multi-modal embeddings are generated by some fusion method and finally decoded for the downstream task being solved [2]. However, MNER has the following two properties that make it unsuitable for this paradigm: 1. Semantic correlation between images and text is generally low. Unlike other multi-modal tasks such as image-text generation and multi-modal entity alignment, there is not necessarily a high correlation between the text to be recognized and the corresponding descriptive image in MNER. Since the mainstream datasets were created based on social media, even the recognized entities may not be represented at all in the images, which hinders multi-modal interaction. 2. The classes of named entities are different from the labels of the dataset on which the training of the visual feature extractor is based. Mainstream visual encoders are trained on datasets such as ImageNet [3] and COCO [4], where labels differ significantly from named entities. This makes it difficult for the visual encoder to accurately localize targets in the image that are related to named entities.


"Discussing the legacy of *Iron Man*, ..."
MARVEL LEGACY
INVINCIBLE IRON MAN
IRON MAN #593
THE SEARCH FOR TONY STARK

Movie [MISC]   *Comic* [MISC]   *Character* [PER]

Figure 1: Example of the multi-modal named entity recognition. Different description images will directly affect the entity recognition results

Considering the above characteristics, some researchers [5] have tried to adopt the Text-Text (T+T) paradigm, i.e., to transform images into similar semantic texts through object detection, image captioning or Optical Character Recognition (OCR), and regard these texts as external knowledge to assist the training of the model. Since Text-Text have similar feature space and attention computation among them, the effect is superior to multi-modal joint training when the modal transformation works well. On this basis, recent works [6,7] have demonstrated that adding context-related information to the entities can significantly facilitate named entity recognition, so researchers utilized knowledge bases and large language models (LLMs) to provide external knowledge.

Nevertheless, the current methodologies continue to exhibit certain shortcomings. First and foremost, the majority of previous research has failed to address the issue of insufficient image-text correlation in MNER datasets. The introduction of image-related embedding or external knowledge into the text embedding during subsequent decoding, regardless of the initial correlation between image-text pairs, introduces additional noise. Concurrently, the conventional "I+T" methodology of dual-stream image-text embedding fusion or the "T+T" approach, which entails inputting concatenated text into a Transformer-based encoder, inevitably gives rise to issues such as dispersed attention coefficient calculation and coarse-grained modal interaction. This presents a challenge to the effective integration of auxiliary knowledge into the target entity embeddings. The efficacy of employing LLMs for named entity recognition has been demonstrated to be, at least to date, somewhat less than that of traditional Transformer-based models [7]. However, the current approach of leveraging large models to acquire external knowledge inputs both image captions and text to be recognized as prompts into the LLMs, which may result in redundant recognition and cognitive confusion. In addition, erroneous recognition results produced by the LLM will contribute to the introduction of further noise into the external knowledge.

To address the above issues, we propose MMAVK, a multi-modal named entity recognition model with auxiliary visual knowledge and word-level fusion. It aims to extract semantics from images with multi-modal LLM and generate external knowledge that contributes to entity recognition. Furthermore, it performs embedding fusion at the word-level, thus facilitating fine-grained interaction between external knowledge and original text. Specifically, additional auxiliary context related to entities is generated by designing target-specific prompts and feeding them, as well as the images in the image-text pairs to be recognized, into the multi-modal LLM. During the process of modal fusion, any external knowledge generated based on images with an insufficient level of image-text similarity is filtered and deleted in order to minimize the introduction of noise. Concurrently, we forego the conventional "T+T" approach of concatenating the original text with external knowledge for training. Instead, we employ a weighted summation of the each word-embedding with the external knowledge at the word-level. Experimental results demonstrate that MMAVK outperforms or equals the state-of-the-art methods on the two classical MNER datasets, even when the LLMs employed have significantly fewer parameters than other mainstream models.

2 Related Work

Considering that images and texts are typically presented in pairs on social media, and images can serve as a valuable supplementary indicator for entity recognition in text, an increasing number of researchers have endeavored to integrate visual modality into named entity recognition. Early work on MNER was primarily focused on the generation of low-dimensional embeddings of images and texts through single-stream or dual-stream encoders, followed by the utilization of various cross-modal fusion techniques to facilitate inter-modal interactions and enhance the quality of the joint multi-modal embedding.

Moon et al. [8] first introduced a deep image network to integrate visual modalities. They employed a generic modality attention module to extract the most informative semantics by ascertaining the relative importance of each modality. Yu et al. [9] proposed a multi-modal interaction module to capture the interaction between textual and visual modalities for the purpose of improving the quality of the embedding. Furthermore, they have devised a unified multi-modal Transformer for encoding both the textual embedding and the visual embedding. Zhang et al. [10] adopted a multi-modal semantic graph integrating visual and textual embeddings to investigate the potential semantic links between visual objects and text, and stacked multiple graph-based multi-modal fusion layers for encoding. Jia et al. [11] treated MNER as a machine reading comprehension task, and facilitated the alignment of textual entities with visual regions by designing query terms to acquire prior knowledge. Zhang et al. [10] constructed the image-text pairs to be recognized as a unified multi-modal graph and iteratively performed semantic interactions between nodes to generate the final embedding representation. Wang et al. [12] extended entity label words through an external knowledge base, and measured the salience of features based on the correlation between these extended terms and features. Subsequently, the saliency scores of the features are employed to adjust the cross-modal attention weights through a gate mechanism.

To address the issue of inadequate cross-modal interaction between visual and textual embeddings, Wang et al. [5] proposed a transformation of the visual modality into the textual contexts sharing the same semantic through integrated methods of image captioning, object detection, and OCR. The fusion of embeddings belonging to the same vector space served to alleviate the pressure of multi-modal alignment. Wang et al. [6] retrieved pertinent knowledge about the input image-text pairs from an external knowledge base and transmitted the retrieved results to the language model and the visual model for prediction. The Mixture of Experts (MoE) module, which integrates the predictions of the two models, was then utilized to make the final determination. Li et al. [7] introduced the large language model into the MNER, where image captions and original text were formatted as prompts to be fed into the LLM, promoting it to generate auxiliary context related to entity recognition.

However, the previous methods mentioned above have difficulties in better finding the contextual information related to textual entities within the knowledge base, which can lead to the introduction of irrelevant noise or errors. Additionally, the issue of low image-text correlation in MNER presents a challenge in accurately localizing the visual regions associated with textual entities from the visual modality.

3 Method

We follow previous work in treating MNER as a sequence labeling task, i.e., for a given pair of to-be-recognized image-text pairs $\{X, I\}$, where $X = \{x_1, x_2, \ldots, x_n\}$ is a sequence of target text with n tokens, the model aims to output a sequence of predefined labels $Y = \{y_1, y_2, \ldots, y_n\}$ corresponding to X. We encourage multi-modal LLM to extract the contextual semantics of the images I which are relevant to entity recognition by designing target-specific prompts and generating the corresponding auxiliary knowledge. In order to achieve fine-grained modal interactions, a word-level multi-modal fusion method is employed instead of the text concatenation mechanism used in the traditional text-text model. This method fuses each word-embedding obtained using a Transformer-based encoder with external knowledge. In view of the insufficient semantic relevance of the image-text pairs in the datasets, we have devised a filtering mechanism based on image-text similarity, with the aim of reducing the fusion weight of auxiliary knowledge whose similarity falls below a specified threshold. The overall model architecture is shown in Fig. 2.

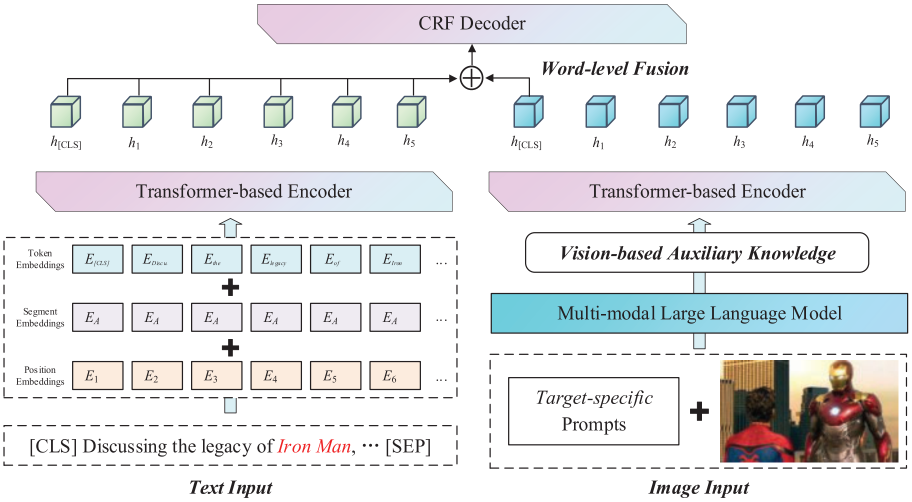


Figure 2: The overall model architecture of MMAVK

3.1 *Vision-Based Auxiliary Knowledge Generation*

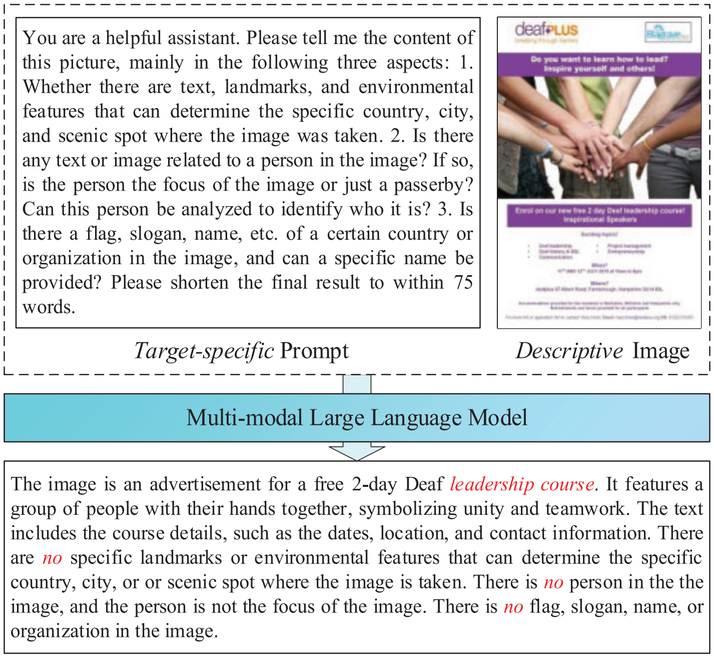
Considering the better modal interaction effect between the same modalities, we follow the "T+T" multi-modal fusion approach, expecting to transform visual modalities into textual modalities without changing the semantics. At the same time, researches [6,7] have demonstrated that in the case of insufficient in-sample information, auxiliary external semantic knowledge can effectively enhance text comprehension. Accordingly, for the visual data, we input it into MLLM for comprehension and encourage the model to generate the most relevant auxiliary knowledge for named entity recognition by providing target-specific prompts. The generation schema is shown in Fig. 3.

Previous work [7] on acquiring external knowledge based on LLM utilized the multi-modal pre-trained model to generate the caption of the descriptive image, and then fed the image caption, the text to be recognized, and the designed prompts together into the large model. This approach presents three inherent limitations.

(i) It is difficult to balance the importance played by visual modality and textual modality in large model generation. The semantic information conveyed by the visual modality in the prompt is limited to a single sentence describing the image, this may result in the loss of crucial details, such as optical characters, objects, and other pertinent elements, within the image. Nevertheless, if object recognition or OCR technologies are employed in advance to obtain image details and used in conjunction with the image caption, the resulting prompt will be overly reliant on visual modality, which may impede the recognition of the text.

(ii) An excessive reliance on the generative effects of multi-modal pre-trained models. As a semantic alternative text to the image schema, this approach presupposes its high semantic similarity to the original image. Consequently, it places considerable demands on the efficacy of the multi-modal pre-trained model. In the event that the effect of the multi-modal pre-trained model is inadequate, the potential for error propagation is significantly heightened.

(iii) The use of the text as the content of the prompt results in cognitive confusion and the emergence of redundant recognition issues. It has been demonstrated that named entity recognition using large language models is, in general, less effective than Transformer-based models [7]. Consequently, if the generated auxiliary knowledge contains erroneous results identified by LLMs, it will inevitably result in an increase in noise.



You are a helpful assistant. Please tell me the content of this picture, mainly in the following three aspects: 1. Whether there are text, landmarks, and environmental features that can determine the specific country, city, and scenic spot where the image was taken. 2. Is there any text or image related to a person in the image? If so, is the person the focus of the image or just a passerby? Can this person be analyzed to identify who it is? 3. Is there a flag, slogan, name, etc. of a certain country or organization in the image, and can a specific name be provided? Please shorten the final result to within 75 words.

deafPLUS
Do you want to learn how to lead? Inspire yourself and others!
Enrol on our new free 2 day Deaf leadership course! Inspirational Speakers

Target-specific Prompt

Descriptive Image

Multi-modal Large Language Model

The image is an advertisement for a free 2-day Deaf *leadership course*. It features a group of people with their hands together, symbolizing unity and teamwork. The text includes the course details, such as the dates, location, and contact information. There are *no* specific landmarks or environmental features that can determine the specific country, city, or or scenic spot where the image is taken. There is *no* person in the the image, and the person is not the focus of the image. There is *no* flag, slogan, name, or organization in the image.

Figure 3: The generation schema of vision-based auxiliary knowledge

Considering the above issues, our goal is to leverage the extensive knowledge of image-text comprehension embedded within the MLLM to extract detailed information from the descriptive image at a fine-grained level. The objective is to convert the visual modality into text while maintaining the original semantics of the image to the greatest extent possible. This allows the model to improve the quality of vision-based textual contexts applied to the "T+T" paradigm, while adding additional external auxiliary knowledge:

$$Aux = MLLM(prompt, I). \tag{1}$$

It is important to note that the MNER dataset classifies entities into four categories: locations, people, organizations, and other. Accordingly, we encourage the MLLM to direct particular attention to the four categories of targets present in the images. The objective is to prompt the MLLM to focus on a range of visual elements, including optical characters, maps, landmarks, attractions, people, faces, flags, slogans, and names, in order to ascertain the image's relevance to a specific location, person, or organization.

In order to avoid the problem that the lack of correlation between images and text results in auxiliary knowledge that does not contribute to the recognition of textual entities. We additionally employ the multi-modal pre-trained model CLIP [13] to encode the original image-text pairs $\{X, I\}$ and calculate the semantic similarity between them:

$$Textemb = CLIP_{TextEncoder}(X), \tag{2}$$

$$Imageemb = CLIP_{ImageEncoder}(I), \tag{3}$$

$$Sim = cosine(Textemb, Imageemb). \tag{4}$$

To mitigate the error transmission caused by the low semantic relevance of the descriptive image to the text to be recognized, due to factors such as the presence of noise in the dataset or the low quality of the image itself. During the subsequent knowledge fusion phase, we assign a lower weight to auxiliary knowledge that exhibits image-text similarities below a pre-established threshold, thereby reducing the impact of noise introduced by such knowledge.

3.2 Named Entity Recognition

Unlike previous work based on the "T+T" paradigm where the original text sequence $X = \{x_1, x_2, \ldots, x_n\}$ is concatenated with the auxiliary knowledge $Z = \{z_1, z_2, \ldots, z_m\}$ as $X' = \{x_1, x_2, \ldots, x_{n+m}\}$ and then fed into a Transformer-based encoder to leverage the attention mechanism to extract valuable information from the auxiliary knowledge. For more fine-grained modal interactions, we first embed the original text $X = \{x_1, x_2, \ldots, x_n\}$ individually by the Transformer-based encoder:

$$H = \{h_1, h_2, \ldots, h_n\} = embed(\{x_1, x_2, \ldots, x_n\}), \tag{5}$$

where h_i is the word-embedding of the ith token, containing the semantics of the word in the whole sentence.

For the corresponding auxiliary knowledge $Z = \{z_1, z_2, \ldots, z_m\}$ of original text X, we also utilize the Transformer-based encoder for processing, but employ its pooling outputs to obtain global semantics. Specifically, prior to feeding auxiliary knowledge into the encoder, additional markers, namely $[CLS]$ and $[SEP]$, are added to the beginning and end of the sequence, respectively:

$$Z' = \{[CLS], z_1, z_2, \ldots, z_m, [SEP]\}, \tag{6}$$

where $[CLS]$ represents the output of the final transformer layer and is utilized to characterize the entirety of the input sequence, $[SEP]$ is used to demarcate the end of a sentence and the beginning of another.

Subsequently, the modified auxiliary knowledge sequence is encoded, and the embedding of $[CLS]$ is extracted to aggregate the knowledge of the entire sequence. This embedding is then fed into a fully connected layer and activated to obtain the final auxiliary knowledge embedding h_{aux}:

$$\{h_{[CLS]}, \ldots, h_{[SEP]}\} = embed(\{[CLS], z_1, z_2, \ldots, z_m, [SEP]\}), \tag{7}$$

$$h_{aux} = tanh(Linear(h_{[CLS]})). \tag{8}$$

$Linear$ means the fully connected layer, and $tanh$ is activation function.

The traditional "T+T" paradigm generally adopts the knowledge fusion approach where the text to be recognized is concatenated with auxiliary text and fed into a transformer-based encoder to generate word embeddings for all tokens (including those of the auxiliary text), followed by decoding only the word embeddings of the text to be recognized. However, given that MNER is a token-by-token task, this approach struggles to accurately extract knowledge from the entire auxiliary text that is relevant to specific word embedding. Consequently, we have adopted an innovative word-level multi-modal fusion method.

Specifically, after obtaining the word-embeddings of each token to be recognized and the global embedding of auxiliary knowledge using the same transformer-based encoder, we dynamically fuse each word-embedding with the auxiliary knowledge embedding through a linear layer-based weighted summation, thereby facilitating the deep involvement of high-quality auxiliary knowledge in the decoding phase:

$$h_i^{'} = \boldsymbol{W}[h_i, h_{aux}], \tag{9}$$

$$H' = \{h_1^{'}, h_2^{'}, \ldots, h_n^{'}\}, \tag{10}$$

in which $\boldsymbol{W}$ is the weight matrix and H' is the final joint embedding.

Following the previous work, we feed the final joint embedding H' into the Conditional Random Field (CRF) to calculate the probability of a predicted label sequence:

$$p(y|H'; \theta_{CRF}) = \frac{\prod_{i=1}^{n} S_i(y_{i-1}, y_i, H')}{\sum_{y_i \in Y} \prod_{i=1}^{n} S_i(y_{i-1}^{'}, y_i^{'}, H')}, \tag{11}$$

$$L = -\sum_{i=1}^{n} log\,(p\,(y_i|H'; \theta_{CRF})), \tag{12}$$

where $S_i(\cdot)$ is a potential function, Y is a set of all possible label sequences, θ_{CRF} is a set of parameters which define the potential function and the transition score from the label y_{i-1} to the label y_i. CRF can reasonably model context dependencies in natural languages and ensure global consistency of sequences, and thus have significant advantages and are widely used in serialization annotation tasks.

4 Experiments

In this section, we will report the experiment details including datasets, parameter settings, baselines and the results. We conduct experiments to answer the following four questions about MMAVK:

(1) Question 1 (Q1): Has MMAVK shown improvement compared to the previous baselines?
(2) Question 2 (Q2): Does the auxiliary knowledge we generate prove more effective than other external knowledge?
(3) Question 3 (Q3): Is the word-level modal fusion approach we use superior to the traditional approach?
(4) Question 4 (Q4): Whether filtering out visual information with low image-text similarity benefits MNER?

4.1 Datasets

We conduct experiments on two public MNER datasets: Twitter-2015 [14] and Twitter-2017 [1]. The details of Twitter-2015 and Twitter-2017 can be found in Table 1.

Table 1: The details of Twitter-2015 and Twitter-2017

Ent. type	Twitter-2015			Twitter-2017		
	Train	Val	Test	Train	Val	Test
[PER]	2217	552	1816	2943	626	621
[LOC]	2091	522	1697	731	173	178
[ORG]	928	247	839	1674	375	395
[MISC]	940	225	726	701	150	157
Total	6176	1546	5078	6049	1234	1351
Tweets	4000	1000	3257	3373	723	723

4.2 Experimental Setup

MMAVK was trained on a single NVIDIA RTX 3090 GPU. The proposed approach was implemented using Python 3.8.0, PyTorch 1.7.1, and CUDA 12.1. During model training, we used the AdamW optimizer to minimize the loss function L. The learning rate was incrementally augmented to its maximum within the first 10% of the gradient update via a linear warm-up, followed by a linear decay for the remainder of the training period. The weight decay for all non-biased parameters was set to 0.01, the batch size was set to 16, and the maximum number of training epochs was set to 30. After each epoch, the model exhibiting the most favorable validation results was saved and subsequently evaluated.

MMAVK chooses the backbone of RSRNET [15] without the visual processing module as the vanilla MNER model. Qwen2-VL-7B-Instruct [16] as an open-source multi-modal LLM from Alibaba that is capable of handling arbitrary image resolutions, is selected to be the auxiliary knowledge generator. It demonstrates effective multi-modal comprehension and generation capabilities while utilizing fewer parameters. We utilized its original version without fine-tuning for multi-modal knowledge comprehension and generation. In the case of using a single NVIDIA RTX 3090 GPU to run the MLLM for auxiliary knowledge generation, the average processing time for a single image is 14.739 s, occupying 16,450 MB of GPU memory. For filtering the auxiliary knowledge, we adopt CLIP [13] with ViT-B/32 to compute the semantic similarity between the original image-text pairs. We elect to utilize the same encoder XLM-RoBERTa-large [17], as that employed in ITA [5], PromptMNER [18], CAT-MNER [12], MoRe [6] and PGIM [7] for a fair comparison.

4.3 Baselines

We compared our MMAVK against several previous state-of-the-art models, including both uni-modal and multi-modal approaches, to demonstrate its superiority. For uni-modal text-based approaches, we consider: CNN-BiLSTM-CRF [19], HBiLSTM-CRF [20], BiLSTM-CRF [21], BERT-CRF [22], BERT-SPAN and RoBERTa-SPAN [23].

For multi-modal text-based approaches, we consider: UMT [9], UMGF [10], MNER-QG [11], R-GCN [24], ITA [5], RSRNeT [15], PromptMNER [18], CAT-MNER [12], MoRe [6], and PGIM [7]. UMT proposes a unified transformer architecture that integrates multi-modal data streams, leveraging entity spans to refine final prediction outcomes. UMGF adopts a unified multi-modal graph to represent the input sentences and images to capture the semantic relationships between graph-text pairs. MNER-QG extracts the prior knowledge about entity types and visual regions with query grounding for enhancing representations. R-GCN focuses on gathering the image information most relevant to image-text pairs in the dataset through inter-modal and intra-modal relation graphs. RSRNeT is designed to facilitate a more comprehensive extraction of visual features based on object detection techniques, incorporating a multi-scale visual feature extraction module. ITA proposes to adopt the "T+T" paradigm, where the visual context generated from the image after object recognition, image caption, and optical character recognition is concatenated with the original text then be inputted into the language model for training. PromptMNER computes the correlation between the image and each entity-related prompt using a multi-modal pre-trained model, thus extracting entity-related visual clues with corresponding weights. CAT-MNER proposes to refine cross-modal attention by identifying and highlighting certain features whose salience is measured according to their relevance to extended entity tag words in an external knowledge base. MoRe retrieves relevant knowledge about the image-text pairs in an external knowledge base and inputs the results into the language model and the visual model for prediction, respectively, and combines the predictions of the two models through an Mixture of Experts module. PGIM introduces a Multi-modal Similar Example Awareness module that sets a small number of samples in a fixed format so as to generate the most relevant prompts. This prompts ChatGPT to generate auxiliary knowledge heuristically, thereby improving the efficiency of entity prediction.

4.4 Main Results

To answer Q1, we compared MMAVK against several previous state-of-the-art models on NER, the main experimental results are shown in Table 2. In comparison to previous models, except for PGIM, MMAVK exhibits a distinct superiority. Furthermore, when only visual information is used as the basis for auxiliary knowledge and a large model with 7B parametric quantities is employed as the auxiliary knowledge generator, some of the metrics of MMAVK remain superior to those of the PGIM, which utilizes GPT-3.5-Turbo to process image-text pairs simultaneously to generate auxiliary knowledge.

Table 2: The main results of MMAVK against other baseline methods on two datasets

Models	Twitter-2015							Twitter-2017						
	Individual category (F1)				Overall			Individual category (F1)				Overall		
	PER	LOC	ORG	OTH.	Pre.	Rec.	F1	PER	LOC	ORG	OTH.	Pre.	Rec.	F1
							Uni-modal							
BiLSTM-CRF	76.77	72.56	41.33	26.80	68.14	61.09	64.42	85.12	72.68	72.50	52.56	79.42	73.43	76.31
BERT-CRF	85.37	81.82	63.26	44.13	75.56	73.88	74.71	90.66	84.89	83.71	66.86	86.10	83.85	84.96
BERT-SPAN	85.35	81.88	62.06	43.23	75.52	73.83	74.76	90.84	85.55	81.99	69.77	85.68	84.60	85.14
RoBERTa-SPAN	87.20	83.58	66.33	50.66	77.48	77.43	77.45	94.27	86.23	87.22	74.94	88.71	89.44	89.06
CNN-BiLSTM-CRF	–	–	–	–	66.24	68.09	67.15	–	–	–	–	80.00	78.76	79.37
HBiLSTM-CRF	–	–	–	–	69.22	74.59	71.81	–	–	–	–	83.32	83.57	83.44
							Multi-modal							
UMT	85.24	81.58	63.03	39.45	71.67	75.23	73.41	91.56	84.73	83.24	70.10	85.28	85.34	85.31
UMGF	84.26	83.17	62.45	42.42	74.49	75.21	74.85	91.92	85.22	83.13	69.83	86.54	84.50	85.51
MNER-QG	85.68	81.42	63.62	41.53	77.76	72.31	74.94	93.17	86.02	84.64	71.83	88.57	85.96	87.25
RSRNET	–	–	–	–	75.83	77.35	76.48	–	–	–	–	87.55	88.21	87.90
R-GCN	86.36	82.08	60.78	41.56	73.95	76.18	75.00	92.86	86.10	84.05	72.38	86.72	87.53	87.11
ITA	–	–	–	–	–	–	78.03	–	–	–	–	–	–	89.75
PromptMNER	–	–	–	–	78.03	79.17	78.60	–	–	–	–	89.93	90.60	90.27
CAT-MNER	88.04	84.70	68.04	52.33	78.75	78.69	78.72	94.61	88.40	88.14	**80.50**	90.27	90.67	90.47
MoRe$_{\text{MoE}}$	–	–	–	–	–	–	79.21	–	–	–	–	–	–	90.67
PGIM	88.34	84.22	**70.15**	**52.34**	**79.21**	79.45	79.33	**96.46**	89.89	**89.03**	79.62	**90.86**	**92.01**	**91.43**
MMAVK (ours)	**90.54**	**86.47**	68.14	50.65	78.66	**81.07**	**79.85**	95.98	**89.92**	87.30	78.14	90.36	91.03	90.69

Note: Bold indicates the best result, underlined is second best.

To demonstrate the effectiveness of the auxiliary knowledge generation method utilized in this paper and answer Q2, we obtained the auxiliary knowledge generated in PGIM and MoRe, and then conducted experiments with the network and fusion approach employed in this study, without similarity-based filtering. The results are shown in Table 3. When all factors are held constant, the auxiliary knowledge generated in this paper has the best contribution to the named entity recognition results.

Table 3: Performance comparison of MMAVK using different auxiliary knowledge

Models	**Twitter-2015**			**Twitter-2017**		
	Pre.	**Rec.**	**F1**	**Pre.**	**Rec.**	**F1**
MMAVK-MoRe$_{\text{Text}}$	75.85	77.63	76.73	87.95	88.02	87.98
MMAVK-MoRe$_{\text{Image}}$	74.56	79.18	76.80	85.13	87.58	86.34
MMAVK-PGIM	77.80	**79.85**	78.81	88.20	89.43	88.81
MMAVK$_{100}$	**78.07**	**79.85**	**78.95**	**88.85**	**90.10**	**89.47**

Note: Bold indicates the best result.

Following the training approach in RSRNET [15], four distinct multi-modal fusion approaches were evaluated using XLM-RoBERTa-base as the encoder to answer Q3: (1) The "T+I" paradigm, in which visual features are used as prefixes to the textual information in each self-attention layer of the encoder. (2) Discarding visual features and using only textual features. (3) The traditional "T+T" paradigm, in which visually generated text is concatenated with the original text into the encoder. (4) The word-level multi-modal fusion method proposed in this paper. As evidenced by the experimental results presented in Table 4, our proposed word-level multi-modal fusion approach exhibits a notable superiority. It was unexpected that the model employing the "T+I" paradigm exhibited inferior performance compared to the model encoding solely textual features. One potential explanation for this is that a text-focused sequence tagging task, such as named entity recognition, is challenging to learn fine-grained modal interactions from different vector spaces. The investigation of the "T+T" paradigm will continue to be a significant avenue of inquiry in the field of named entity recognition.

Table 4: Performance comparison of MMAVK using different multi-modal fusion approaches

Models	**Twitter-2015**			**Twitter-2017**		
	Pre.	**Rec.**	**F1**	**Pre.**	**Rec.**	**F1**
MMAVK (T+I)	73.90	74.78	74.34	86.12	86.82	86.47
MMAVK (T-only)	73.95	76.86	75.37	86.67	87.12	86.90
MMAVK (Con.)	74.33	76.59	75.44	86.26	86.45	86.36
MMAVK	**75.25**	**77.32**	**76.27**	**87.31**	**88.08**	**87.69**

Note: Bold indicates the best result.

To verify the effectiveness of the similarity-based filtering mechanism (Q4), we set the thresholds to different percentages to filter the auxiliary knowledge for the experiments, respectively. For the auxiliary knowledge whose image-text similarity is lower than the threshold, its fusion weight was set to 0. The mean similarity of image-text pairs in Twitter-2015 calculated based on CLIP is 0.3038 and the median is 0.3047, while the mean similarity is 0.3011 and the median is 0.3022 in Twitter-2017. So we first searched for the best threshold value using 0.3 as an anchor point. Optimal results were achieved at a threshold of 0.35, which subsequently served as the new anchor for further optimization. As shown in Fig. 4, filtered auxiliary knowledge generally facilitates entity recognition better than unfiltered auxiliary knowledge, and the facilitation is best when the threshold is set to 0.35. However, this is only the result of experiments on these two datasets and is not proof that 0.35 is the optimal threshold we are looking for. The selection of the threshold depends on the encoder used and the quality of the dataset. We did not find a clear correlation between the threshold setting and F1, and the optimal threshold is not a specific point such as the mean or median of similarity. More research and experiments are still needed on how to better filter the noisy information in the visual modality through the filtering mechanism. In our future work, we will try to find a reasonable dynamic threshold selection mechanism for different types and sizes of datasets.

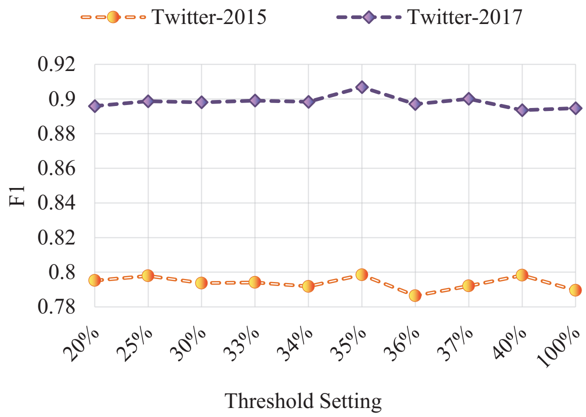
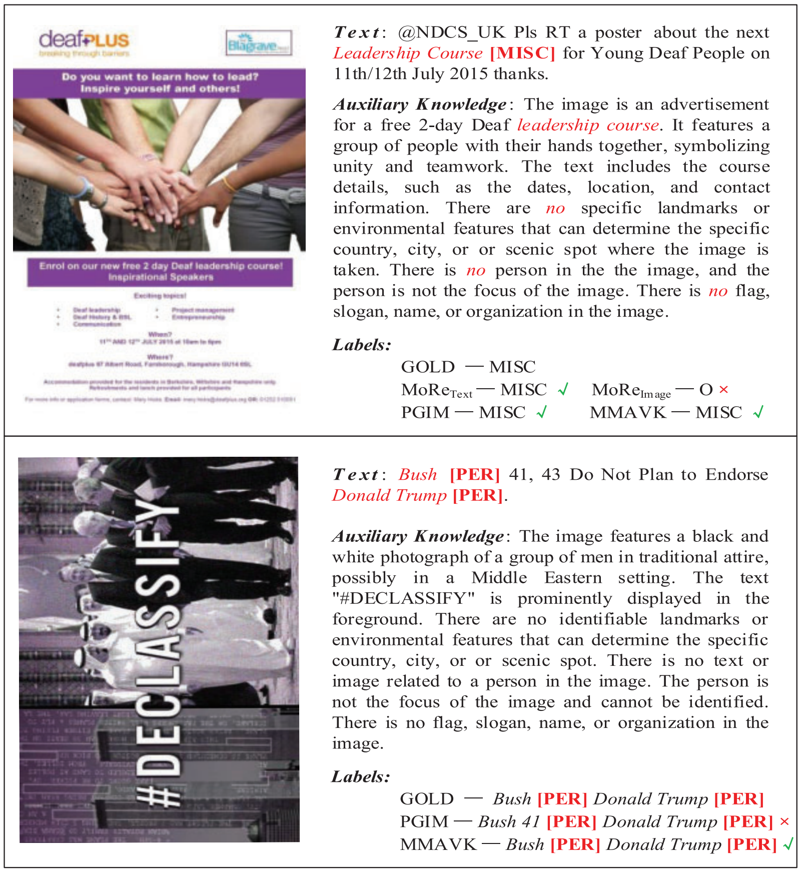


Figure 4: The impact of different filtering thresholds on MMAVK

4.5 Case Study

We select case studies shown in Fig. 5 to illustrate the potential benefits of auxiliary knowledge for enhancing the performance of a model. $\text{MoRe}_{\text{Text}}$ and $\text{MoRe}_{\text{Image}}$ employ text- or image-related knowledge retrieved from Wikipedia, whereas PGIM utilizes auxiliary knowledge generated by ChatGPT, which is prompted based on image-text pairs to be recognized. By analyzing the visual information, the vision-based auxiliary knowledge generated by the multi-modal LLM contains the context associated with the textual entities present in the visual modality. Visual elements related to locations, people, and organizations serve as the foundation for decoding and classifying entities.

However, there is a possibility that the adoption of external knowledge may introduce additional errors. For models that use retrieval-based external knowledge acquisition mechanisms, poor retrieval methods or low-quality knowledge bases have resulted in a large amount of useless or erroneous information in the acquired external knowledge. For models that use large model generation capabilities to generate external knowledge, the performance of the large model itself and the quality of the dataset are important factors in ensuring the quality of the external knowledge. For example PGIM may introduce misidentification results from large models, such as treating “Bush 41” as a whole entity and generating a context that causes the model to misidentify “Bush 41” as [PER]. Our proposed auxiliary knowledge generation method does not involve the participation of the text to be recognized, while a filtering mechanism is used to remove low-quality visual information. The errors present in the generated auxiliary knowledge are minimized. The extensive knowledge of the LLM offers a wealth of external information for MNER, while its robust natural language processing capabilities enable highly precise a priori entity recognition. Since some of the metrics of PGIM are still better than MMAVK, we also tried to input the original text into the LLM to obtain its pre-recognition labels and context using different prompts. This information, along with the vision-based auxiliary knowledge generated in this paper, was then input into the model. However, none of these attempts achieved the expected results.



Text: @NDCS_UK Pls RT a poster about the next *Leadership Course* **[MISC]** for Young Deaf People on 11th/12th July 2015 thanks.

Auxiliary Knowledge: The image is an advertisement for a free 2-day Deaf *leadership course*. It features a group of people with their hands together, symbolizing unity and teamwork. The text includes the course details, such as the dates, location, and contact information. There are *no* specific landmarks or environmental features that can determine the specific country, city, or or scenic spot where the image is taken. There is *no* person in the the image, and the person is not the focus of the image. There is *no* flag, slogan, name, or organization in the image.

Labels:

GOLD — MISC
$\text{MoRe}_{\text{Text}}$ — MISC ✓ $\text{MoRe}_{\text{Image}}$ — O ×
PGIM — MISC ✓ MMAVK — MISC ✓

Text: *Bush* **[PER]** 41, 43 Do Not Plan to Endorse *Donald Trump* **[PER]**.

Auxiliary Knowledge: The image features a black and white photograph of a group of men in traditional attire, possibly in a Middle Eastern setting. The text "#DECLASSIFY" is prominently displayed in the foreground. There are no identifiable landmarks or environmental features that can determine the specific country, city, or or scenic spot. There is no text or image related to a person in the image. The person is not the focus of the image and cannot be identified. There is no flag, slogan, name, or organization in the image.

Labels:

GOLD — *Bush* **[PER]** *Donald Trump* **[PER]**
PGIM — *Bush 41* **[PER]** *Donald Trump* **[PER]** ×
MMAVK — *Bush* **[PER]** *Donald Trump* **[PER]** ✓

Figure 5: Two practical examples demonstrating the enhancement effects of visual auxiliary information on recognition

5 Conclusion

To address the problems of poor image-text correlation and low efficiency of external knowledge acquisition in MNER, we propose MMAVK, a multi-modal named entity recognition model with auxiliary visual knowledge and word-level fusion. It aims to extract semantics from images through the multi-modal LLM and generate vision-based auxiliary knowledge that contributes to entity recognition. Furthermore, it performs embedding fusion at the word-level, thereby facilitating fine-grained interaction between external knowledge and original text.

We believe that LLMs, especially multi-modal LLMs, remain one of the key techniques for improving the effectiveness of MNER. However, as we argue in Section 4.5, prompting LLMs to generate more and more fine-grained auxiliary information does not directly lead to improved model performance. In future work, we will focus on how to better utilize large models to remove noise in visual modalities irrelevant to entity recognition and to improve the quality of the auxiliary knowledge while mitigating the errors associated with erroneous entity recognition results from LLMs.

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Availability of Data and Materials: The data that support the findings of this study are available from the corresponding author, Huansha Wang, upon reasonable request.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

Abbreviations

MNER	Multi-modal named entity recognition
LLM	Large language model
MLLM	Multi-modal large language model
MMAVK	Multi-modal named entity recognition model with auxiliary visual knowledge and word-level fusion
CRF	Conditional Random Field
OCR	Optical Character Recognition

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